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Reverse Logistics Simulation in a Second-Hand Goods Company

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Abstract. This paper proposes to use an agent-based simulation model approach to evaluate the performance of multiple potential reverse logistics strategies for a second-hand goods company. This organization faces a strong growth in an urban context and must plan its operations to both collect and deliver goods from and to every site. The agent-based simulation technique is used in order to first make an assessment of the current operations and then to evaluate potential reverse logistics strategies in different growth scenarios. Envisaged strategies concern modifications either to the trucks fleet, to the time of sites visit or to the policy in place to collect and deliver goods. The key performance indicators used in this study are the travel time per day, the distance travelled and CO2 emissions. Also, this paper shows another practical application of the use of CO2 emissions databases to simulate environmental implications of different scenarios, based on the types of trucks used and the drive cycles. Based on the results of the different strategies evaluated, recommendations are presented.

Keywords. Reverse logistics, agent-based simulation, second-hand, route optimization.

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1. Introduction

This paper proposes a simulation approach to evaluate potential reverse logistics strategies to reduce the reverse logistic costs of a second-hand goods company's supply chain. The studied organization is a not-for-profit organization in the retail sector that gives a second life to end-of-life goods by collecting and reselling them. This introduction section proposes an overview of reverse logistics, as well as the specific constraints addressed in this paper.

1.1. Reverse logistics in a second-hand goods

One of the main challenges of reverse logistics lies in the uncertainty related to supply volume and quality. In the context of second-hand goods, the quantity of products donated by people every day is highly variable and presents a high seasonality. This variation and seasonality can be explained in part by external conditions, such as weather or by specific behaviours, such as the annual spring cleaning. Another challenge concerns goods quality. Indeed, part of these goods cannot simply be resold because it would cost more to refurbish them than buying them new. Therefore, second-hand goods companies must optimize their ability and capacity to collect these goods and sort them.

The optimization problem studied in this paper is that of a non-profit organization based in Montreal, Quebec, which operates in high-density urban conditions. This paper develops and uses a hybrid simulation platform to analyze the performance of several logistics strategies in order to optimize its future operations.

The logistics network of this organization consists of donation centers, donation boxes, stores and one distribution center. The organization collects donations from its many donation centers and boxes, and ships them to its distribution center, before it distributes them to its stores. Different types of empty and full bins are also transferred to donation centers, stores and its distribution center. To simplify vehicle routes planning, these logistic activities are currently carried out independently (i.e., no pick-ups and deliveries on the same route), and all donations are transferred through the distribution center before being shipped to their designated stores.

1.2. Objectives

The objective of this paper is to assess different logistic strategies using a hybrid discrete event and agent-based simulation model, while considering different growth scenarios. Because there are a limited number of strategies to assess, simulation was used in order to easily cope with the high variability of donations. First, Section 2 presents the relevant literature. Next, Section 3 introduces the simulation model. Finally, based on the carried out simulation experiments, an evaluation of the impact of different logistics strategies in the context of multiple growth scenarios is presented. Performance is evaluated in terms of overall transportation distance, average travel time per day, and CO_2 emissions.

2. Literature review

Supply chains consist of suppliers, manufacturers, distribution centers and stores Supply chain logistic strategies have been extensively studied in the retail business. For example, Zhang (2009) studies the impact of pull flow vs. push flow in various contexts. Watanarawee (2010) studies the benefits of a fully integrated IT strategy combined with product-tracking technologies, while others, such as Ryu (2009) explain the long-term benefits of creating strategic partnership across the supply chain.

2.1. Reverse logistics

Reverse logistics starts where the traditional supply chain ends, namely when the end customer buys the product. According to the Council of Logistics Management, reverse logistics is "used to refer to the role of logistics in recycling, waste disposal, and management of hazardous materials; a broader perspective includes, all issues relating to logistics activities to be carried out in source reduction, recycling, substitution, reuse of materials and disposal" (De Brito, 2004). It takes its roots in the reuse of end-of-life products, either to transform them into usable by-products, or to extract raw material and create completely different products. Olshavsky (1985) explains that customers must dispose of their end-of-life products in the best possible way. For them, recycling products is linked to their willingness to reduce the long-term environmental impact of their mode of consumption and to achieve sustainable development (Sarkis, Helms, & Hervani, 2010). The term "green logistics" has emerged and is used to designate the

awareness of the environment in a reverse logistics context (Guoyi, 2011). The recycling of domestic products is a good example of an everyday application of reverse logistics. The interested reader is also referred to Dekker *et al.*, (2012) for a review of optimization technics in green logistics.

Rogers and Tibben-Lembke (1999) have proposed a categorization of reverse logistics applications. They either concern the product itself, or its packaging. The authors also present the main activities related to end-of-life products management, including their return to their suppliers, their reselling, their recycling and their reconditioning/refurbishing for resale. Concerning packaging, the main activities include their reuse for another product, their refurbishing for resale, and their recycling to use as raw material. Beyond the need to comply with regulations or their desire to contribute to sustainable development, companies strive to increase the efficiency of their reverse logistics activities, as these activities do not necessarily involve direct added value. However, as mentioned in Section 1, the optimization of these activities is difficult thanks to the intrinsic variable quantity and quality of returned goods (Zhao, 2008). For the interested readers, Maynard *et al.*, (2013) present a case study on the logistics challenges encountered by the non-profit organization Oxfam.

Furthermore, in the context of a second hand goods company, logistics involves both the return of end-of-life product and their distribution for resale. Like in the retail industry, one way to establish a strong customer base is to give customers product diversity. In a second hand goods company, this involves moving frequently unsold items from one store to the other. This entails a constant management of inventories both in terms of rotation and transportation.

2.2. Logistic strategy optimization

In this paper, the design of an efficient logistic strategy involves two distinct challenges. First, because both resources (e.g., trucks, trailers) and processes (e.g., routing constraints, route schedules) can be affected by the strategic design, this project involves solving a common transportation optimization problem known as the vehicle routing problems (VRP). VRP has been studied a lot in scientific literature in operational research because of its multiple applications in our everyday lives (Panapinun &

Charnsethikul, 2005). Laporte (1992) presents a survey of the different solutions to various classes of VRP. This problem is outside the scope of this paper, although routes are used in the model.

Second, because of demand and supply variability, this project also involves the need to assess the impact of variability on logistic performance. Logistics and supply chain optimization can be supported by different methods (e.g., mathematical programming). that are effective to optimize supply chain operations. However, they are either limited or complex to implement when dealing with various sources of uncertainty in complex systems. Here, simulation is appropriate and usually easier to implement. Simulation is used to identify tendencies and recurring behaviours, and analyze the performance of specific solutions in various conditions. This ability to represent stochastic contexts supports making informed decisions even with highly variable attributes. Simulation consists in creating a simplified virtual model of the studied phenomenon. Cartier and Forgues (2006) and (Othman & Mustaffa, 2012) discuss the benefits of simulation.

Agent-based simulation (ABS) is an emergent simulation technique (Macal & North, 2006) that aims at modeling the individual behaviours and interactions of the different entities of a system. Instead of modeling the interconnections between the aggregated components of a system in a sequential manner, such as in discrete-event simulation, ABS focuses on the way the actors of a system react to their environment, influence each other and make decisions related to a constantly evolving context. Barbati *et al.*, (2012) made a survey of the recent literature related to the applications of ABS in an optimization context. Among other applications, ABS can be effectively used in supply chain optimization, by reproducing the behaviour of its main actors. For example, Sauvageau and Frayret (2015) use ABS to study the performance of different supply and production policies in a waste paper procurement supply chain. Similarly, Bollinger *et al.*, (2012) propose an ABS approach to study mobile phone recycling, which is similar to the context of this paper, which involves the collection and delivery of second-hand products, and uncertainties related to the quantity and quality of collected products. The next section presents our hybrid discrete event and agent-based model.

3. Simulation model

The first section presents a general overview of the model developed, while the second section details all components of the model and describes their interactions.

3.1. General overview

The general overview of the model includes many aspects of the reverse logistic problem on hand. The first sub-section describes the company's operating sites.

3.1.1. Supply chain sites

The studied logistic system is essentially composed of five types of sites. The first two types of sites include 21 donation centers and 90 donation boxes. Donation centers are used exclusively to receive donations from people and are strategically located in richer areas to maximize the number and value of donations. There is generally only one working employee per site and his/her task simply consists of receiving and sorting donations. The sorting process is described below. Next, donation boxes are usually located in areas with high pedestrian traffic, such as train stations or commercial centers. People can bring bags of articles to be donated and deposit them in these boxes.

The third type of sites is comprised of 10 stores. They consist of multiple aisles stores where articles are displayed. Stores are strategically located in less privileged areas of the city. They also serve as donation centers.

The fourth type of site is the distribution center, where all donations transit and where trucks start and end their routes. The process at the distribution center is described below. Finally, attached to the distribution center is a liquidation center.

3.1.2. Types of donations

Donations include any types of household objects in good condition, such as clothing, jewellery, furniture, dishes, books, shoes, televisions, tools, and sports equipment. Several types of bins are used to transport these products. Clothes and other specific goods are transported in 50 cubic feet bins. 30% of goods are transported in large bins,

while 70% are transported in small bins. Finally, articles from donation boxes are transported in 50 cubic feet carton boxes called Gaylords.

3.1.3. Product flows

In order to simplify vehicle routes, all donations, except those received directly in stores, transit through the distribution center. Similarly, all goods collected from any donation center are always shipped to the same store. At most, 3 donation centers are associated to each store. Goods collected with donation boxes can be shipped to any store.

In brief, donations are first sorted into hard goods or clothes, and placed in their associated bins. A truck then picks them up, after delivering empty bins to replace the ones that have just been filled. At the same time, another truck picks-up the goods received in donation boxes. All goods are transported to the distribution center, where they are sorted by store to which they will be delivered. Afterwards, trucks deliver the donations to their designated stores, where they are received and stored. There, trucks also collect empty bins. Then, donations are segregated into two categories: saleable products and unsalable products. Unsalable products are products that are too damaged to be sold. On the other hand, saleable products are labeled and displayed. Unsalable products are placed back into bins and returned to the distribution center. There, they can either be exported or simply compacted and trashed.

When products in stores are not sold, they are shipped to another store. This process is called a rotation. After 2 or 3 rotations, if an article is still unsold, it is sent back to the liquidation center. If it remains unsold, it is either exported or trashed. Approximately 50% of donations cannot be sold, and about 30% will go through one or several rotations. The rest is sold at the store where they were initially delivered. Figure 1 and 2 illustrates respectively the process flows and the products and bind flows.

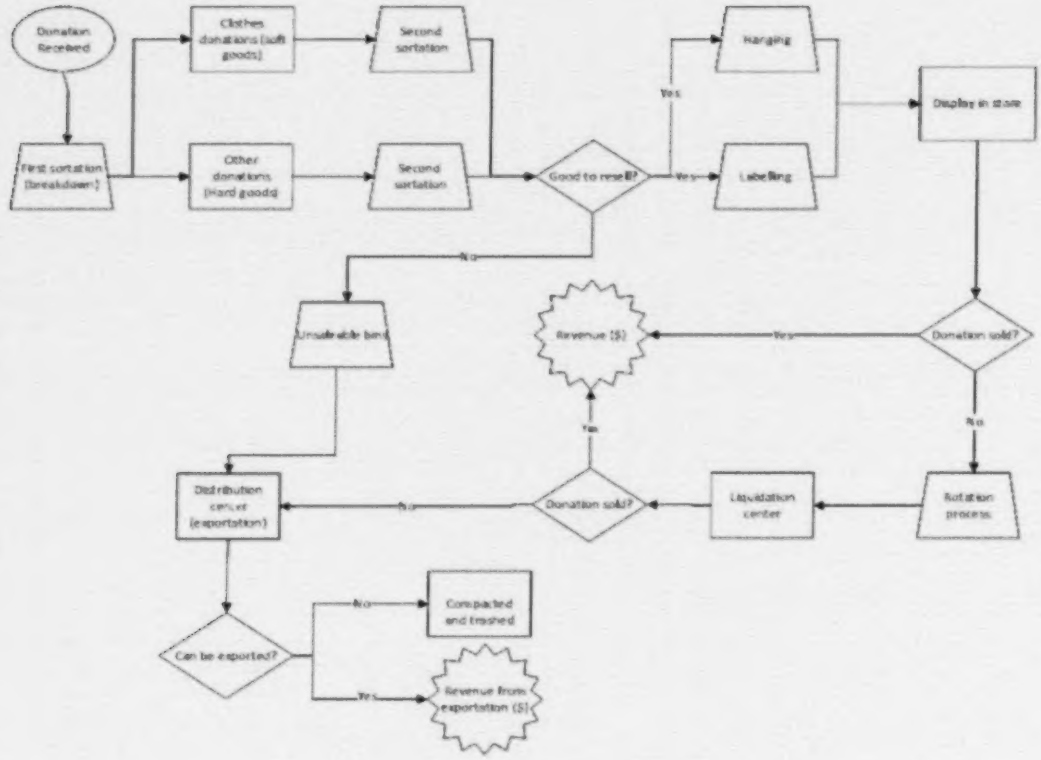


Figure 1: Process flows

Trucks leave the distribution center to resupply the stores fully loaded. Then, they usually come back loaded at 80% capacity with unsalable products and rotations. The remaining capacity includes trash and cartons. Consequently, trucks are always full, which leaves little opportunity for improvement with backhauling strategies.

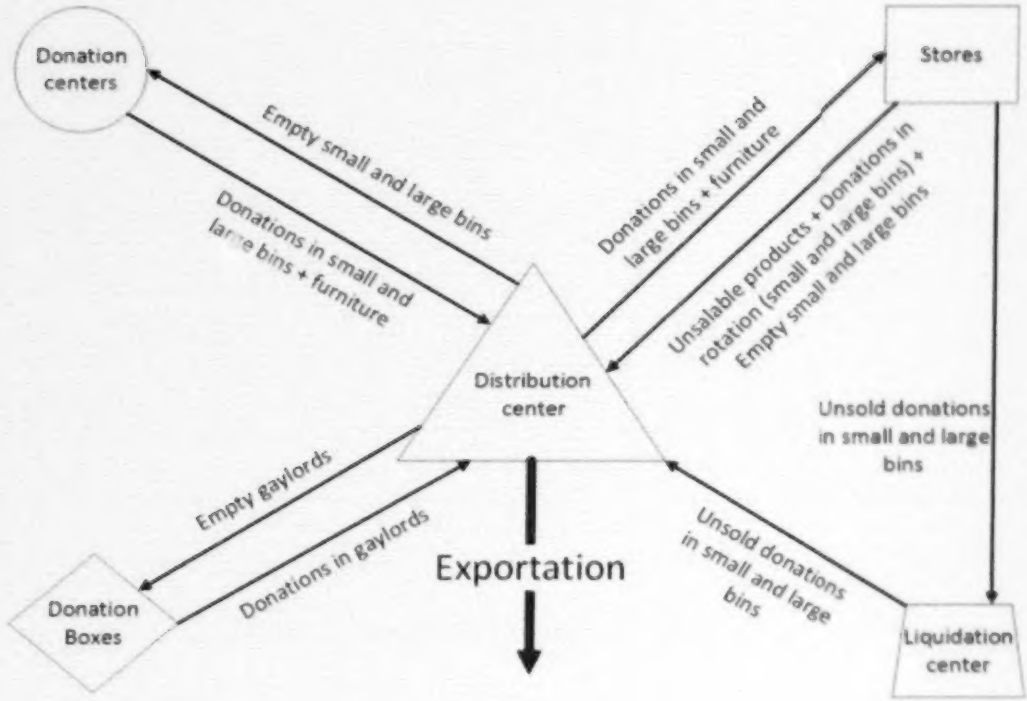

Donation centers
Stores
Empty small and large bins
Donations in small and large bins + furniture
Donations in small and large bins + furniture
Unsalable products + Donations in rotation (small and large bins) + Empty small and large bins
Distribution center
Unsold donations in small and large bins
Empty gaylords
Donations in gaylords
Exportation
Unsold donations in small and large bins
Donation Boxes
Liquidation center

Figure 2: Products and bins flows

3.1.4. Seasonality

The volume of donations presents a strong seasonality. It varies a lot depending on the time of the year. As mentioned in the introduction, people donate according to external conditions such as weather, moving period, and statutory holidays. The monthly variation from the average number of donations is about 30%. Once donations volumes are forecasted, a target inventory level is planned for each store. In order to meet demand during low donation seasons, inventory must be accumulated at the distribution center. Because the market is not saturated, only donations volume forecast, actual inventory levels in the stores, and inventory level target in the distribution center are used to resupply the stores. In the context of this project, actual data from the organization's ERP was used to define accurate donation and demand profiles.

3.1.5. Revenue generation

Based on the data provided by the organization, we observe that the higher the inventory level in stores, the higher the revenue. This relation is almost directly proportional. Figure 3 illustrates this situation by representing the monthly revenue as a function of the number of monthly donations deliveries. A 38% increase of deliveries from the lowest month, generate a similar increase in terms of revenue.

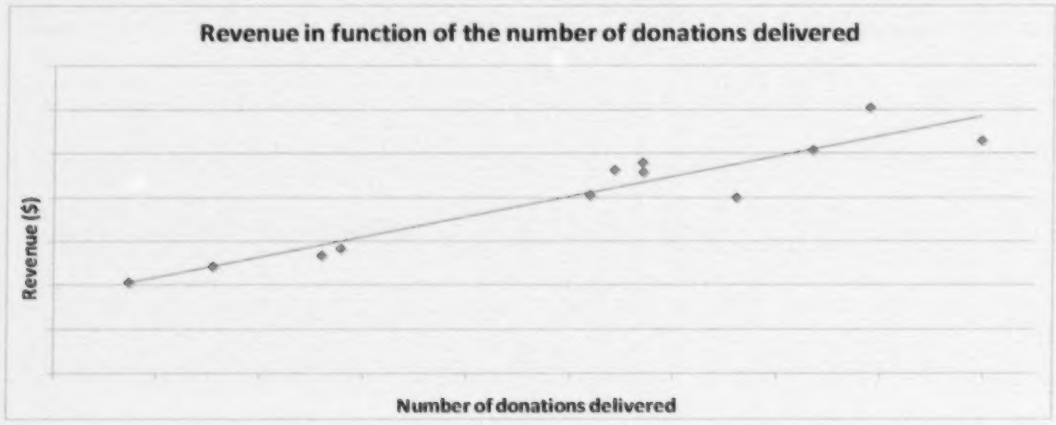


Figure 3: Revenue as a function of the number of donations delivered

3.1.6. Collection and delivery processes

First, donation boxes are managed separately. They are visited at a predetermined frequency that is set and constantly adjusted with historical data. Next, store deliveries are done in the morning, while donation centers are visited in the afternoon. In other words, a donation collected at a donation center in the afternoon transits through the distribution center in order to be delivered to its associated store the next morning.

In this study, a basic VRP algorithm was implemented in order to support the routing constraints of new logistic strategies. In order to maintain good working conditions for truck drivers, the objective function of this algorithm was to minimize the maximum travelling time between routes. In other words, the algorithm aims to avoid having a route with twice the travelling time of another one.

3.2. Model description

This section describes in detail all components of the model and how they were integrated.

3.2.1. Load unit

In order to simplify the modeling of the different types of bins transiting in the system, and because small bins are the most commonly used, the model considers that all bins are small. Thus, a full large bin was modeled as 15 small bins, while an empty large bin was modeled as 30 small bins. For the remaining of this paper, only small bins are considered.

3.2.2. Donation centers agents

Each donation center is modeled as a unique agent where a certain quantity of donations is received each day. The quantity of donations received at each site was modeled using 2014 historical data and analyzed with Statistica (StatSoft). This data was cleaned and analyzed to determine the coefficient of seasonality of each month. Next, a normal, seasonally adjusted, probability distribution describing the volume of donations received was determined for each site. Then, depending on the number of empty bins available at each donation center, the donation center agents compute the number of empty bins needed to maintain a target number of bins. The need for empty bins is proportional to the number of bins filled with donations. Each agent communicates its need to the distributer center agent.

3.2.3. Stores agents

Like the donation centers, stores can receive donations. The same process to calculate the number of donations received was used and modeled. Concerning the target donations inventory level, the 2014 inventory targets data was used to set the simulation target of each store. In order to achieve these target inventory levels, the donations received at the donation centers are delivered to their associated store. However, these deliveries, plus the donations received directly at stores, are not always enough to achieve the inventory target level. If this happens, the store agents define how many bins are required from the

distribution center's stock to meet their target. They send this number to the distribution center agent.

When the donations are delivered at the stores, the sorting process for saleable and unsalable products starts. This process is modeled as a triangular distribution law that was determined in collaboration with the organization. A certain proportion of the bins received are emptied and placed on tables, while the remaining unsalable products are re-loaded into bins in order to be collected by a truck. The store agents send the distribution center agent the number of bins of unsalable products that must be collected.

Of the remaining articles in the stores, some are sold to customers. The proportion of the number of articles sold was also modeled as a triangular probability law. Once sold, these articles exit the model. Other articles, as described in the previous section, are not sold and have to be rotated to other stores. Thus, a certain number of articles that have not been sold is also modeled to be rotated using a triangular probability law. These articles are re-loaded into bins and the store agents send the distribution center agent the number of bins that must be collected for rotation. This process of receiving articles and converting into unsalable products, sold products and rotations also produces empty bins. Consequently, a certain number of empty bins must be collected. This number is also sent to the distribution center agent.

3.2.4. Distribution center agent

The distribution center agent has a central role in the model. It decides how much of the needs of donations centers and stores will actually be fulfilled, depending on many parameters. These parameters include current inventory levels of full and empty bins as well as trucks' capacity. For example, a store asking for a certain quantity of bins to achieve its target might not receive the full quantity on the same day, because there are not enough bins currently in stock. In this situation, the distribution center agent decides to not deliver the same day, but later instead. The distribution center agent also analyses every truck's route and prioritizes the delivery of full bins to stores before the delivery of empty bins to donations centers, in order to maximize revenue generation. Then, the trucks are loaded based on the available inventories. Every time a truck comes back from

visiting a site and needs empty or full bins to complete its route, the available inventory at the distribution center is re-evaluated.

3.2.5. Trucks agents

The organization uses two types of trucks: cube and semi-trailer trucks. For cube trucks, the fleet is composed of 3 trucks of 20' length, 3 trucks of 24' and 1 truck of 26' feet. There is also a 36' semi-trailer truck. These trucks are categorized in two different types, depending on their ability to access every site. 5 of these trucks have a door on the side, while the others have a back door. Some sites can only be accessed by trucks with a side door, because of the street and docks configuration. Also, other sites can only be accessed by small trucks. In order to ensure a proper representation of this reality in the evaluation of the strategies scenarios, these accessibility constraints have been included in the route creation algorithm. Furthermore, each truck has a capacity, which is included in the model as a capacity expressed in equivalent full bins. Along this line, empty bins are modeled as equivalent to half a full bin. Table 1 gives the capacities of all trucks.

Table 1: Capacity of trucks in the fleet

Size of truck	Capacity
CUBE - 20 feet	180
CUBE - 24 feet	270
CUBE – 26 feet	300
SEMI-TRAILER – 36 feet	400

Currently in the organization, collects and deliveries are planned with a fix set of truck routes that presents some slight variations in high and low season. Because of the trucks' capacity, these routes generally visit (i.e., for a pickup or delivery) only one site in high season, and up to 2 to 3 sites in low season.

Finally, before leaving a site, the trucks agents decide how many full and empty bins must be loaded from the distribution center, depending on the sites visited in the corresponding route. For routes with multiple sites, empty bins can be collected at the first site and delivered at the second, reducing the need to load them at the distribution center. Also, all loading decisions at sites are made based on the available capacity of the trucks.

3.2.6. Routes

The organization dedicates a truck to collect the donations boxes, based on their pre-determined frequency of collect. Thus, each day represents a different set of donations boxes to be collected. Because the organization does not plan to change this, the routes dedicated to the donations boxes were not directly modeled. Instead, the volumes of goods originating from donation boxes were modeled as a volume directly entering the distribution center each day, based on 2014 historical data.

Next, the routes for donation centers and stores are divided in two different categories: the morning routes and the afternoon routes. The morning routes aim to deliver donations to the stores, while the afternoon routes aim to pickup donations from the donations centers.

Each route segment is characterized by its distance, which is implemented in the model as an origin-destination matrix calculated with Google Maps. Similarly, each segment is also characterized by a travel time. In order to add precision to the calculation of the travel times, 3 different travel time matrices were implemented to account for the urban logistic context of this logistics problem: day time travel with and without traffic, and night time travel. Therefore, during simulation, when a truck leaves a site, the appropriate travel time is used to travel to the next site. Table 2 describes which matrix is used for each period of the day.

Table 2: Travel times matrices used in the model

Time of the day	**Matrix used for travel times**
6 am – 9 am	Day in traffic
9 am – 4 pm	Day outside traffic
4 pm – 7pm	Day in traffic
7 pm – 6 am	Night

In order to simulate the current situation, the real routes were used while in the context of the simulation, new routes were calculated. A route creation algorithm was developed and used in order to find new optimal routes for every strategy tested and for the growth scenarios. The development of this algorithm is not in the scope of this paper. Based on

the number of bins to be collected and delivered at every site and on the truck's capacity and accessibility constraints, the algorithm generates different sets of routes for each month. It takes as input the average number of bins to be collected and delivered for every site and every month. Its objective is to minimizing the maximum travelling time between routes. Thus, routes are generated offline and then integrated in the simulation.

Trucks also have loading and unloading times integrated in the model. Because of the lack of data, trucks have fix loading and unloading times that were estimated with the organization.

In order to estimate the CO_2 emission of each logistics strategies, we estimated the CO_2 emission levels of each potential segment and each type of drive cycle. First, we estimated fuel consumption as a function of the drive cycle (e.g., highway, urban with traffic). Using Delorme *et al.*, (2009), fuel consumption was modeled as a function of the drive cycle average speed. Figure 4 shows the fuel consumption depending on the drive cycle average speed for the types of trucks used in the model. The 20' trucks are associated to class 2, 24' and 26' trucks to class 6 and the 36' trailer to class 8. Next, matrices of average speed per origin-destination segment were created based on the distance and travel time matrices. To estimate CO_2 emissions for each type of truck, each segment, and each drive cycle, matrices of fuel consumption were calculated, based on the closest speed point in Figure 4. With three matrices of travelling time and three types of trucks, we created nine different matrices of fuel consumed per segment. These fuel consumption matrices were then transformed in CO_2 emission quantity, with 1 liter of diesel = 2.7 kg.CO_2 (Natural Resources Canada, 2009). Therefore, in the simulation, each time a truck leaves a site, the total CO_2 emission is increased by the value corresponding to this segment in the appropriate table.

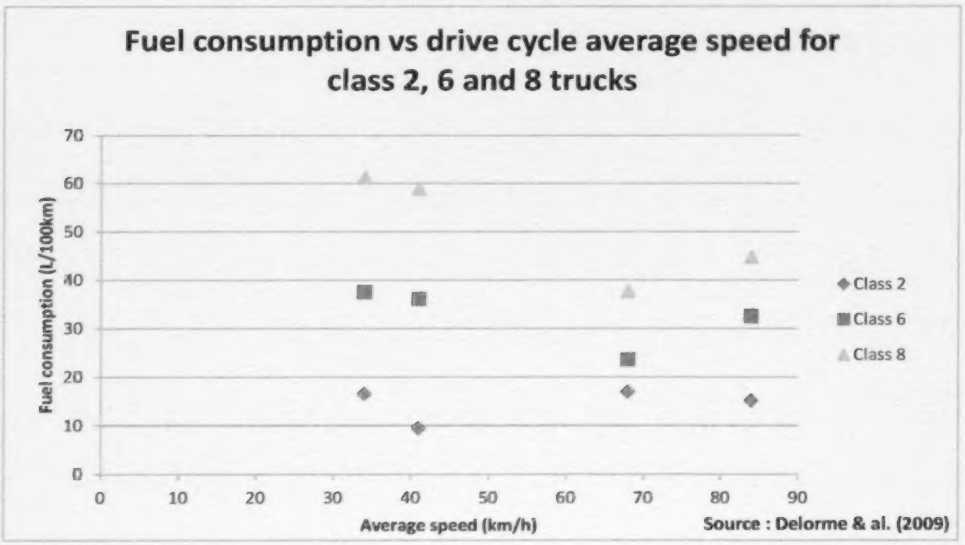


Figure 4: Fuel consumption vs. drive cycle average speed for class 2, 6 and 8 trucks (Delorme *et al.*, 2009)

4. Methodology and experiments

This section describes the methodology used in order to carry out the different experiments. Section 5 describes the results of these experiments.

4.1. Model Implementation

Many agent-based simulation platforms are capable of implementing the model described above. The *Anylogic* simulation software was used because it is relatively easy to implement hybrid agent-based and discrete event simulation model. Furthermore, it can be used to implement specific functions based directly in JAVA.

4.2. Model setup and validation

The model was developed and setup with the support of the partner organization. Information and data were gathered through interviews, historical data, as well as public scientific reports (i.e., for CO_2 emissions) and Google Maps. In order to validate the model, different outputs of the model were compared to actual data. Validation experiments were carried out by doing ten replications of the base scenario (i.e., current

logistics strategy with current input functions). Two types of output were observed: independent variables (i.e., statistical input functions) and dependent variables (i.e., resulting performance indicators). This allowed us to observe that independent parameters are well adjusted and modeled, and that the simulation model is well calibrated.

More specifically, the independent variables that were validated include the number of goods received at each site, the percentage of unsalable items and the percentage of sold items. Concerning the dependent variables, we validated the total revenues as well as the stores' inventory levels at the end of each day. First, the simulated total revenues was calculated based on the average value of a single good sold and was compared to historical sales reports for 2014. These validation experiments confirmed that the model simulates accurately not only the flow of products entering and exiting the system, but most importantly the process of revenue creation as a function of the number of goods received per site and available at stores. Next, the stores' inventory level was also validated with the total number of bins remaining at the stores each day. Because the organization does not hold any data on on-hand inventory, it was only qualitatively compared with the support of the partner organization. This validation served as another confirmation that the model simulates accurately customer demand as a function of the available stock in stores, as well as the flow of rotations and unsalable articles. The results of these validation experiments are presented in section 5.1.

4.3. Experimental design and methodology

In collaboration with the partner organization, we assessed the operational performance of the current logistics strategy and defined potential strategies. All strategies were evaluated with respect to 3 different growth scenarios, including the base scenario (current data), 10% growth and 20% growth. Table 3 describes all experiments made and the growth scenarios tested.

Table 3: Design of experiments

	Logistics strategy tested	Growth scenario
#1	Current logistics strategy	Base, 10% growth, 20% growth
#2	Partial delivery and pickups during night shift	Base, 10% growth, 20% growth
#3	Use of 2 36' trucks in the afternoon	Base, 10% growth, 20% growth
#4	Pickup and directly delivery to stores	Base, 10% growth, 20% growth

In Table 3, the experiment of the current logistic strategy in the base scenario was used for model validation. In other words, it represents the current situation (i.e. with the current input of goods received and the current demand from stores). The organization currently observes about 8% annual growth. Therefore, the 10% growth scenario represents the actual growth, while the base scenario is a pessimist scenario and 20% growth is an optimistic scenario. Concerning growth scenarios in the organization, growth is mostly (i.e., 70%) achieved by adding new sites, while 30% of the growth comes evenly from the current sites. In order to be coherent with this, the 10% and 20% growth scenarios involve the addition of 3 new donations centers, and 1 new store, strategically located to develop new markets. Also, in order to be coherent with the current fleet management policy, the creation of these new sites necessitates the use of an additional truck. Therefore, both growth scenarios were designed with the support of the organization. In the 10% growth scenario, the same routes are used, with the addition of the new donation centers being visited by a 20' truck (class 2) and the new store by the semi-trailer (class 8). Concerning the 20% growth scenario, the new donation centers are visited by a 26' truck (class 6) instead. Table 4 summarizes the changes in the model implied by each growth scenario.

Table 4: Changes implied by each growth scenario

Description	Growth scenario		
	Actual	10% growth	20% growth
Number of sites	31	35 (1 add. store + 3 donations centers)	35 (1 add. store + 3 donations centers)
Number of goods donated per day	X	X2 = X + 10%, with 30% from current sites and 70% from new sites	X3 = X2 + 10%, with 30% from current sites and 70% from new sites
Number of trucks used	3	4	4
Types of trucks used	Class 2 : 1 Class 6 : 1 Class 8 : 1	Class 2 : 1 Class 6 : 2 Class 8 : 1	Class 2 : 0 Class 6 : 3 Class 8 : 1
Target inventory at each store	I_s	$I_s2 = I_s + 10\%^*$ *with 30% to current stores and 70% at new store	$I_s3 = I_s2 + 10\%^*$ *equally applied among all 11 stores
Daily inventory target at distribution center	I_{dc}	$I_{dc}2 = I_{dc} + 10\%$	$I_{dc}3 = I_{dc}2 + 10\%$

The testing of the current logistics strategy with the 3 growth scenarios serves as a base case scenario to which the other scenarios are compared. These tests aim at assessing the logistics performance of the current strategy and at creating status quo data (i.e., if the strategy does not change) to assess the performance of the new strategies.

Because the urban context has a strong influence on travel times, the second experiment aims at evaluating the potential benefits of partially collecting and delivering the sites during the night. Municipal laws do not allow trucks to circulate at night in certain areas, which prevent visiting some sites at night. Therefore, this experiment includes night routes only for the sites that can be visited and other routes for the remaining sites during the day. Sites are visited by the same trucks as during the day.

The next experiment aims at assessing a strategy with a different fleet of trucks. Currently, the 36' trailer is only used in morning routes for deliveries. However, the growth of the organization requires using bigger trucks to collect and deliver each site with only one visit per day. Thus, this experiment evaluates the benefits of using 2 36'

trucks in the afternoon instead of the smaller trucks. With this strategy, new routes are calculated and added in the model for the afternoon.

The fourth experiment aims to assess the impact of including both pickups and delivery in the routes. In the current strategy, all goods transit through the distribution center and are thus handled many times. Thus, this strategy aims to evaluate the impacts of collecting donations and delivering them directly to stores, using the current fleet of trucks. However, the goods collected from the donation boxes and stored at the distribution center still require to be shipped from the distribution center. New routes were developed specifically for this.

All experiments were replicated 10 times with a horizon of 365 days. There are four different strategies tested with 3 growth scenarios, for a total of 120 simulation runs. Also, because historical data is used to initiate the simulation, warm-up period is negligible.

4.4. Key performance indicators

Finally, in order to assess the performance of the current logistic strategy and evaluate the impact of the experiments on the organization's performance, several key performance indicators (i.e. KPI) were developed in collaboration with the industrial partner. The KPIs used are the total annual distance, the total time for collection and delivery per day and the total emissions of CO_2. More details of these KPIs can be found in Appendix A.

5. Results and analysis

This section first presents the validation results of the model. Next, the results of all experiments are presented and analyzed.

5.1. Model validation

We validated 2 different elements of the model: the generated statistical input parameters, and the general behaviours of the model. Because it is the most important parameters from which the entire simulation depends on, the number of donations received was compared to the 2014 historical data used to create the statistical distributions. An

average monthly difference of 2.3% with real data was observed in low season and of -0.8% in high season, which is acceptable.

Next, in order to validate the general behaviour of the model, two elements were validated. First, the revenue function was compared to historical sales reports for 2014 (see Figure 5). This analysis confirms that the modeled revenue creation process (i.e., revenue as a function of the number of goods received per site) of the simulation model is accurate. Furthermore, revenues per month had an average difference of 1.7% with historical data, which is, again, acceptable.

The second general element validated is the remaining inventory level at the end of each day in stores. Thus, the number of goods remaining in stock at the end of a business day in stores was analyzed as a percentage of the total goods received during that day. An average of 32% of the goods received remains in stock at the end of each day. The partner organization validated qualitatively this element, which was evaluated at 30% of the total goods received. This overall validation allowed us to pursue the remaining experiments.

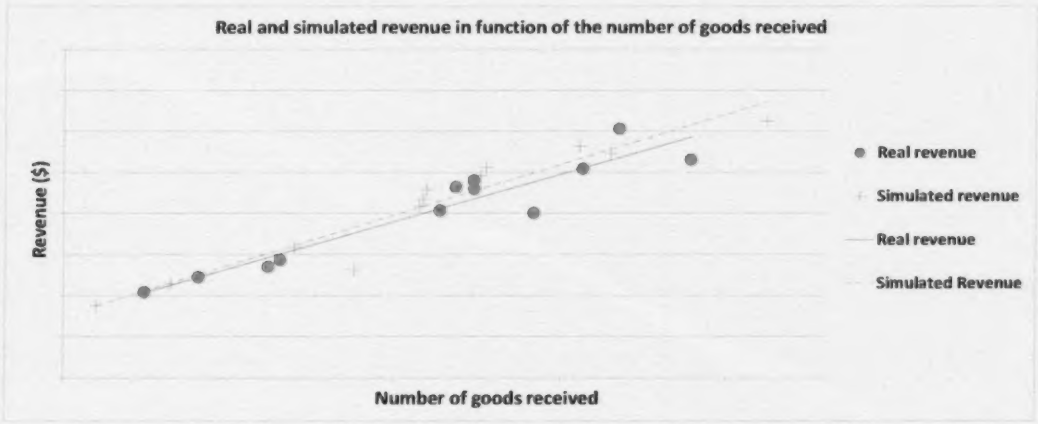


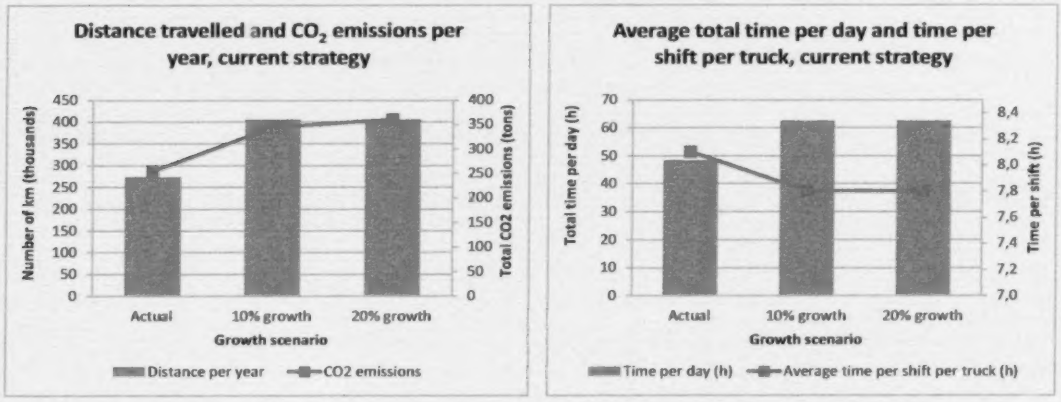
Figure 5: Real and simulated revenue in function of the number of goods received

5.2. Experimental results and analysis

The results for every strategy are shown in this section and analyzed with respect with the KPIs defined previously.

5.2.1. Current strategy

The current strategy experiments serve as a base case to which the other strategies are compared. Figure 6 presents the results for the current logistics performance.



(a) (b)

Figure 6: (a) Distance travelled and CO_2 emissions, delivery at night, (b) total time per day and per shift, delivery at night

As shown in Figure 6a, the total travelled distance per year is about 270.000 km, for an average of 23.9 km per site, and increases to 400.000 km for an average of 31.3 km per site with the new sites in 10% and 20% growth. This increase is due to the fact that the new sites are farther than the current sites. Also, this 48% increase of distance travelled only result in a 35% increase in CO_2 emissions. This is because there are more sites visited by smaller trucks (class 2), which have a lower fuel consumption. In the 20% growth scenario, in which the small truck capacity is not sufficient to haul the total demand, a bigger truck (class 6) is used instead. This causes a 4.7% increase in the CO_2 emissions for the same travelled distance.

Next, as shown in Figure 6b, the current strategy has an average of 48h of total travel time in current conditions, which increases by 29% for both the 10% and 20% growth, up to 62h. In other words, the travel time per visited site increases from an average of 1.5h per site to 1.8h. Again, this is due to the longer average site distance. However, the average time per shift per truck decreases by 4%, from 8.1h to 7.8h. Therefore, the

additional truck for the 10% and 20% growth scenarios, which include four new sites, leads to a little less travel time for all routes.

Table 5: Average truck utilization and latest stores delivery time in current strategy

Description	Growth scenario		
	Current	10% growth	20% growth
Average truck utilization	73.8%	77.1%	79.5%
End of store deliveries	11h30	12h15	12h15

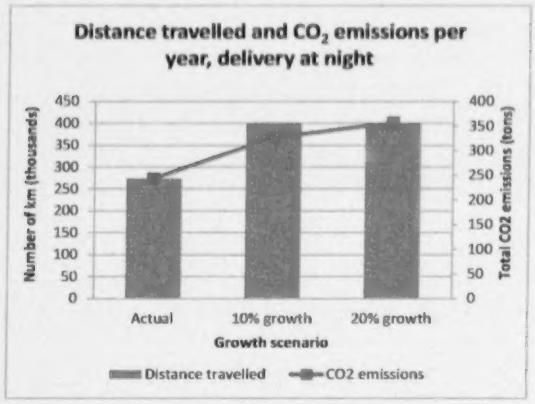
Table 5 shows that the current average truck utilization is about 74%. Furthermore, some items are not considered in the experiments, such as trash and cartons. As a result, if we only consider only the bins, there is in practice a higher truck utilization, which leaves little room to absorb growth with the current fleet. Also, these results are based on a perfect usage of the trucks' capacity, while it might not necessarily be the case in reality. Indeed, some bins can be overfilled, which affects the ability to pile them up and reduces the available truck capacity. Also, the second type of bins (i.e., the bigger bins) was modeled as an equivalent number of small bins when in reality, the large bins might not always be filled up at 100%, which also results in lost space.

Similarly, the average truck utilization increases by 3.3% in the 10% growth scenario and by 2.4% in the 20% growth scenario. Because 30% of the 10% growth comes from current sites, we can expect a 3% increase in truck utilization for the same routes. The difference can be explained by the fact that truck utilization for the new routes (i.e., to the new sites) is higher in the 10% growth scenario than in 20% growth, for which a bigger truck is used.

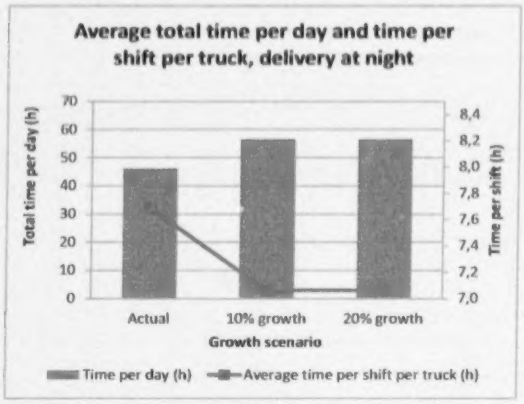
Finally, in the current strategy, in which the stores are delivered in the morning, the latest time of stores delivery is at 11h30 and increases to 12h15 with an additional store, based on a shift start time of 6h.

5.2.2. Delivery and Collect at night

In this strategy, most sites are visited during the night, and others are not due to municipal restrictions. These sites are visited in the morning instead. Figure 7 summarizes the results.



(a)


Average total time per day and time per shift per truck, delivery at night
Total time per day (h)
Time per shift (h)
Actual
10% growth
20% growth
Growth scenario
Time per day (h)
Average time per shift per truck (h)

(b)

Figure 7: (a) Distance travelled and CO_2 emissions, delivery at night, (b) total time per day and per shift, delivery at night.

Here, the distance travelled is the same as in the current strategy. However, the total CO_2 emissions are lower than in current strategy because the drive cycles contain less stop-and-gos. In the current conditions, CO_2 emissions are 4% lower in the delivery at night strategy than in the current strategy. Concerning the 10% growth scenario, the 48% increase in distance travelled result in a 34% increase of CO_2 emissions, which is about the same increase as in current strategy. Concerning the 20% growth scenario, CO_2 emissions are higher (i.e., 9.4% more than 10% growth scenario) because of the use of a class 6 truck for the new sites (higher fuel consumption). This causes emissions to be almost equal in both strategies at 20% growth.

Concerning the total travel time per day, the scenario with the current conditions has a total travelled time of 46.1h, which is 5% smaller than the current strategy. Both the 10% and 20% growth scenarios result in a total travelled time of 56.5h, which is 9.4% smaller than the current strategy. Thus, the opportunity of improvement of this strategy increases

with the number of sites and the distance travelled. The average time per shift also follows the same rule, with a decrease of 4% with the current conditions, and a decrease of 10% with both growth scenarios.

Table 6: Average truck utilization and latest stores delivery time, delivery at night

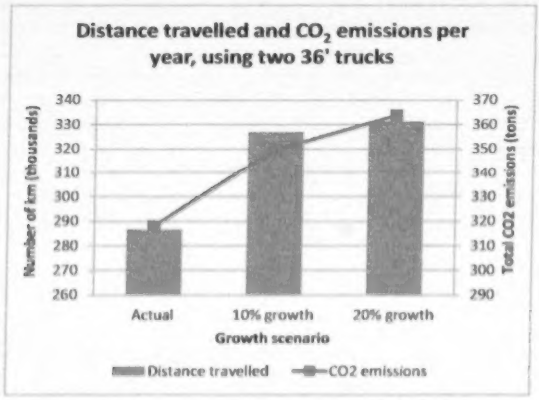
Description	Growth scenario		
	Current	10% growth	20% growth
Average truck utilization	70.2%	74.2%	76.9%
End of store deliveries			
Stores accessible at night (start at 20h)	0h15	1h	1h
All other stores (start at 6h30)	8h	8h	8h

Table 6 shows that the average truck utilization during the night is also around 75% for night deliveries. However, it is slightly lower than the current strategy because routes were modified to meet municipal regulations. The latest delivery time for the sites that can be visited during the night shift varies between 0h15 and 1h, while the other stores are delivered before 8h (truck restriction ends at 7h). Here, although some stores cannot be delivered during the night, all stores can still be visited early in the morning and before the opening.

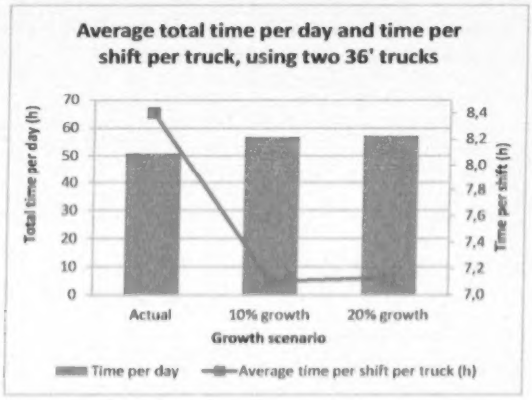
In brief, the delivery at night strategy improves travel time by 5% to 10%. However, this strategy involves modifying and creating new schedules for direct labour and supervision, as well as adding a night premium for employees. Furthermore, the night access to the sites must also be take care of by either entrusting the truck drivers with the keys, or by adding a night shift at the sites, which has other consequences.

5.2.3. Use of 2 36' trucks in the afternoon

This strategy enables combining several donations centers in the same routes. It implies using the 36' truck currently used in the morning routes for stores, plus buying or leasing another one. Figure 8 shows the results for this strategy.



(a)



(b)

Figure 8: (a) Distance travelled and CO_2 emissions, using two 36' trucks, (b) Average total time per day and per shift, using two 36' trucks.

As opposed to the first two strategies, the distance travelled increases slightly for both growth scenarios (respectively 14% and 15.5%), because the higher demand at each site lowers the capacity to optimize routes (i.e., trucks are fully loaded more quickly). This shows that having more sites (25% more sites in afternoon routes) results in better routes optimization. Compared to the base case, the distance travelled in the current conditions scenario is 5% higher in this strategy. This can be explained by the fact that routes are computed in order to minimize the maximum travelling time. However, with more sites to visit, the distance travelled is lower than in the current strategy with respectively 19% and 18% for the 10% and the 20% growth scenarios.

Using 2 36' trucks in the afternoon routes instead of none also has a significant impact on CO_2 emissions (i.e., higher fuel consumption). In the current condition scenario, emissions are 25% higher than in the base case. Each travelled km releases in average 1.1 kg, as opposed to 0.9 kg in the base case. Adding more sites also has a significant impact on CO_2 emissions. The increased distance travelled in both growth scenarios increases CO_2 emissions to the same level than the base case, even if the distance travelled is 19% lower.

Next, the total time per day is 50h in the current condition scenario. It is 5% higher than in the base case not only because the distance travelled is 5% higher, but also because

this distance is partially made in traffic conditions. However, the total time per day in both growth scenarios only increases by 12%. In these scenarios, the total time is 9% less than in the base case. Similarly, the time per shift is also higher in the current condition scenario, but drops to 7.1h per shift in average in both growth scenarios, which is a bit lower than a regular day shift.

Finally, Table 7 shows that the average truck utilization is about the same than in the base case. Similarly, the latest delivery time to the stores is also the same.

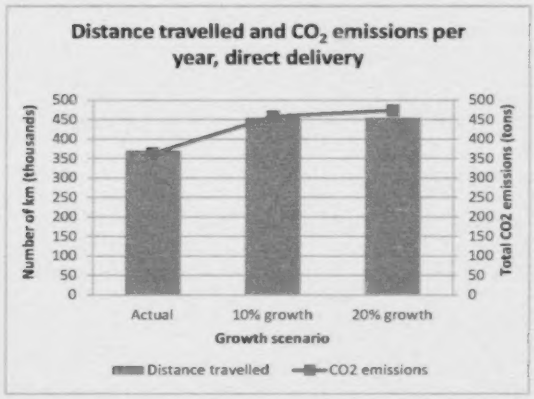
Table 7: Average utilization usage and latest stores delivery time, using two 36' trucks

Description	Growth scenario		
	Current	10% growth	20% growth
Average truck utilization	73.6%	76.2%	79.3%
End of store deliveries	11h30	12h15	12h15

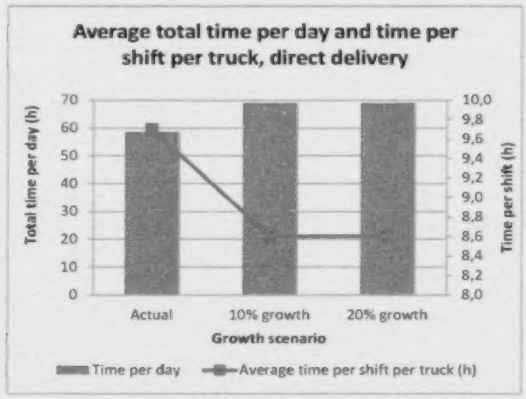
These results show that this strategy is interesting for both growth scenarios in terms of distance travelled and time per day. However, CO_2 emissions are negatively impacted due to higher consumption trucks.

5.2.4. Direct delivery

This final strategy aims at testing the direct collect and delivery of bins from donations centers to their associated stores. In this direct delivery strategy, the small proportion of goods collected in donation boxes still go through the distribution center through a separate route. In order to take into account the fact that the stores are visited more than once (3 times in average), but with less bins to unload/load each time, loading time has been diminished by half. This considers a fix time that cannot be removed. Figure 9 shows the results for this strategy.



(a)


Average total time per day and time per shift per truck, direct delivery
Total time per day (h)
Time per shift (h)
Actual
10% growth
20% growth
Growth scenario
Time per day
Average time per shift per truck (h)

(b)

Figure 9: (a) Distance travelled and CO_2 emissions, direct delivery, (b) Average total time per day and per shift, direct delivery.

The distance travelled is at 370.000 km for current condition scenario and increases to 455.000 km for both growth scenarios (23%). This strategy in both growth scenarios incurs a smaller increase than with the base case because a new efficient route includes the 2 new donation centers and the new store. With this strategy, the distance travelled is much higher (35%) than with the base case, but only 12% higher in the growth scenarios. This can be explained by the fact that, with the current donations centers-stores associations, the current stores are not located near the return journey of the donations centers to the distribution center. Therefore, the detour incurred by a direct delivery increases significantly the distance. In order to optimize this strategy, new associations should be defined in order to optimize the routes.

Concerning CO_2 emissions, the increase in distance travelled increases by 26% and 30% respectively in the 2 growth scenarios (respectively +42%, +33% and +31% with the base case). This difference can be partly explained by the creation of a new route to deliver goods collected at donation boxes, made by a bigger (Class 8) truck.

As Figure 9b also shows, this increase in distance travelled, also increases travel time per day (58h for the current condition scenario, and 69h for both growth scenarios). Concerning working conditions, this is also well above a normal working day (between

9.6h and 8.6h). Therefore, this strategy requires either an additional truck driver or an increase of the drivers' shift.

In summary, the direct delivery strategy results in much higher distances and time required for current condition scenario. However, the difference shrinks in the growth scenarios specifically because of the geographical locations of the new sites. Yet, we can also conclude that different donation centers-stores associations could potentially bring better results. However, CO_2 emissions are still much higher. On the other hand, although the distance travelled is higher than in base case, the direct delivery strategy does not require as much inventory space. It also reduces direct handling costs.

Table 8: Average truck utilization and latest stores delivery time, direct delivery

Description	Growth scenario		
	Current	10% growth	20% growth
Average truck utilization	66.1%	69.3%	72.1%

Finally, Table 8 shows that the average trucks utilization is less efficient than in all other strategies. Concerning the latest store delivery time, it is not relevant because stores are the last sites visited in this strategy. Direct delivery also has an impact on product availability in stores; inventory levels are more likely to be smooth because of more frequent deliveries (with fewer goods) than with the base case (where the highest inventory level is in the morning).

6. Discussion and conclusion

This paper proposes an hybrid agent-based simulation approach to assess the current logistics performance of a non-profit organization and study the impact of new strategies. Several growth scenarios were studied. The complexity incurred by the simultaneous pick-up and deliveries context and the inherent variability of donations justifies a simulation approach. A model was developed to simulate all processes and behaviours as accurately as possible.

The strategies studied involved either a change in the moment of deliveries or collects, a change in the fleet management or, on a higher level, a change in the way the sites are

visited. The KPIs used for comparison were the distance travelled, the travel time per day and the CO_2 emissions.

The main conclusion is that the current strategy is the best one in the current conditions. However, the other strategies show good potential benefits in both growth scenarios. With the historical 10% growth, these strategies can reduce up to 30% of the distance travelled and up to 22% of the travel time. However, they also incur higher CO_2 emissions than the current strategy. The best short-term strategy is to start using 2 36' trucks in order to visit not only the stores, but also the donations centers. The route optimization of this strategy incurs significant potential benefits.

However, the results of these experiments only represent a portion of the possible options of this reverse logistics network. For example, the observed improvements only come from small variations of travelling time and sites visit frequency. Further analysis could explore optimization techniques to improve loading and unloading time. Also, our model does not integrate total costs, which forces us to discard the direct delivery strategy because savings in inventory space requirement are not included. Further research could also include the development of a route optimization algorithm that can find optimal routes based on the time of the day the sites are visited.

On a different token, this study also demonstrates that it is possible to use databases on CO_2 emissions to simulate environmental impacts of different scenarios, based on different truck types and drive cycles. Also, using a more extensive set of data on fuel consumptions, or even using a drive cycle simulator embedded within the agent-based simulation, would strongly improve the accuracy of the simulation of CO_2 emissions.

Overall, the model achieves the initial objectives. However it also presents some limitations that were not considered. For instance, in Canada, travelling times can vary substantially depending on the season, where average speeds in winter are much slower than in summer. Also, donations boxes were aggregated as a simple input of donations directly to the distribution center. They were not integrated into the routes calculations. This was justified partly because of their high number, but mainly because no strategies considered any changes in their management.

Finally, this paper shows that agent-based simulation can be an effective way to study and identify the best logistics strategies for an organization, and the trade-offs between the different performances indicators.

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Appendix A: Key performance indicators definition

The three KPIs used in the model are defined in this section. The first KPI is the total distance made by trucks in the year and is defined in Equation (1). This KPI is calculated for the entire year.

$$Total\ distance = \sum_{i \in S} \sum_{j \in S} \sum_{c \in C} Distance_{i,j} * R_{c,i,j} \quad (1)$$

with

C is the set of trucks used in this strategy and growth scenario;

S is the set of sites contained in this strategy and growth scenario;

$Distance_{i,j}$ is the distance between the site i and the site j;

$$R_{c,i,j} = \begin{cases} 0 & \text{if the truck c did not take the route between sites i and j;} \\ 1 & \text{if the truck c took the route between sites i and j;} \end{cases}$$

The next KPI is the total time per day for delivery and collection, as defined in Equation (2). This KPI is calculated each day.

$$Total\ time\ per\ day = \sum_{t \in T} \sum_{i \in S} \sum_{j \in S} \sum_{c \in C} (Time_{i,j,t} + Load_i) * R_{c,i,j,t} \quad (2)$$

with

T is the set containing the three periods in the model (traffic, without traffic and night);

$Time_{i,j,t}$ is the travelling time between sites i and j during the period t;

$Load_i$ is the loading/unloading time at site I;

$$R_{c,i,j,t} = \begin{cases} 0 & \text{if the truck c did not take the route between sites i and j during the period t;} \\ 1 & \text{if the truck c took the route between sites i and j during the period t;} \end{cases}$$

The third KPI is the total CO2 emissions made in the year. It is defined by Equation (3).

$$Total\ CO_2 = \sum_{i \in S} \sum_{j \in S} \sum_{c \in C} CO2_{c,i,j,t} * R_{c,i,j,t} \quad (3)$$

with

C is the set of trucks used in this strategy and growth scenario;

S is the set of sites contained in this strategy and growth scenario;

$CO2_{c,i,j,t}$ is the CO_2 emissions made by truck c between the site i and the site j during period t;

$$R_{c,i,j,t} = \begin{cases} 0 & \text{if the truck c did not take the route between sites i and j during the period t;} \\ 1 & \text{if the truck c took the route between sites i and j during the period t;} \end{cases}$$